START-UP OF A CATALYTIC REACTOR BY FUZZY CONTROLLER

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Key Words: Process Control, Fuzzy Control, Start Up, Fuzzy Theory, Catalytic Reactor, Expert System

It is difficult to control the start-up of a packed-bed catalytic reactor with exothermic reaction by conventional controller. In this paper, a controller based on the fuzzy set theory is applied to such a system. The controller treats heuristic rules by fuzzy interpretation, and it is also equipped with adaptive scaling factors. The performance of the controller is experimentally examined with a reactor for the catalytic oxidation of hydrogen.

Introduction

Catalytic reaction systems are notable examples of nonlinear dynamics and are therefore very difficult to control. The difficulties are mainly caused by the fact that the kinetics of the catalytic reactions often involve some uncertainties and vary with changes in operating conditions. Such uncertainties and nonlinearities bring about many difficulties in modeling. For such systems the conventional control scheme based on a linearlized model is not appropriate, and some adaptive features are necessary to compensate for variations in the characteristics of the process. In particular, start-up control is the most difficult task for process engineers because the control performance is directly dependent on the accuracy of the model used.

In practice, the start-up of such systems is often controlled by human operators. They never solve mathematical models in their brains but they can do well. What is the strategy of their control operations? Usually, their control policy may be based on vague thoughts and a qualitative manner of thinking. The remarkable characteristics of manual control are:

1) Flexibility in changing the system
2) Capability of learning about the system through the experience
3) Capability of dealing with uncertain knowledge

Fuzzy set theory[7] is a mathematical tool for treating uncertain information such as linguistic statements. The main concept is that of graded membership. In ordinary crisp set theory, a member is either in or out of a subset. In fuzzy set theory, however, the degree of belonging ranges from 'out' to 'in'. The theory provides a gradual transition from the world of precise and quantitative phenomena to that of imprecise and qualitative concepts. Fuzzy control based on this theory is appropriate to the control of processes[2,4] which cannot be described precisely by a mathematical model. Recently there have been published some experimental applications.[1,3,5] The fuzzy approach represents some aspects of human control policy on computers. Though the modeling by fuzzy theory may not be so precise as physical models, most of the tasks performed by humans likewise do not require a high degree of precision. The control performance of a skilled human operator is satisfactory but the speed and capacity are unfortunately limited for complex and multivariable cases. Thus, as process complexity increases, sophisticated control objectives such as the start-up of a nonlinear process cannot be accomplished without the aid of a digital computer. This paper is concerned with the experimental application of a fuzzy controller to the temperature control of a catalytic reactor. The system concerned is highly exothermic and nonlinear, and thus it is difficult to control by conventional controllers. In fact, we previously applied Model Reference Adaptive Control (MRAC) to the reactor, but the control result for start-up was not sufficient.[6] In the experiments with MRAC, it was difficult to eliminate overshootings. This is mainly because change in the system is too fast for the parameters to be adapted correctly. So another control method is required. The main purpose of this paper is to answer the following questions. Can a fuzzy controller be applied for the control of nonlinear processes such as those in catalytic reactors? Especially, is it able to control the start-up operation? It will be shown in this paper that the answers to these questions are affirmative.

To improve the regulation performance, adaptive scaling of the controller gain is also applied successfully.

Received September 2, 1987. Correspondence concerning this article should be addressed to Y. Yamashita.

1. Experimental Apparatus

The catalytic oxidation of hydrogen on platinum–aluminum catalyst particles is investigated as an example of nonlinear processes. A schematic diagram of the experimental apparatus is shown in **Fig. 1**. The catalyst particles contain 2% platinum and their diameter is about 2 mm. They are packed to 30 mm height in a glass tube of 12 mm diameter. The reactor is set in a bath of polyethylene glycol in which temperature is maintained at a constant value. Nitrogen was used as a carrier gas. Flow rates of nitrogen and oxygen are fixed at 800 and 200 ml/min respectively. Hydrogen gas is controlled by a mass flow controller and is supplied to the reactor in the range from 0 to 50 ml/min. Catalyst temperatures are measured by copper-constantan thermocouples at three locations, spaced at equal intervals along the center axis of the packed bed.

Figure 2 shows the hardware elements of the control system. Two personal computers are used, one for measurement of several outputs and the other for calculating the control algorithm. Inlet flow rates of gases are monitored by digital flow meters. All the interfaces such as ADC, DAC and I/O are handmade. Sampling time is chosen as 30 seconds. The objective of the controller in the present experiments is to adjust the flow rate of inlet hydrogen in such a way that the maximum temperature among three locations in the catalyst bed becomes a desired value.

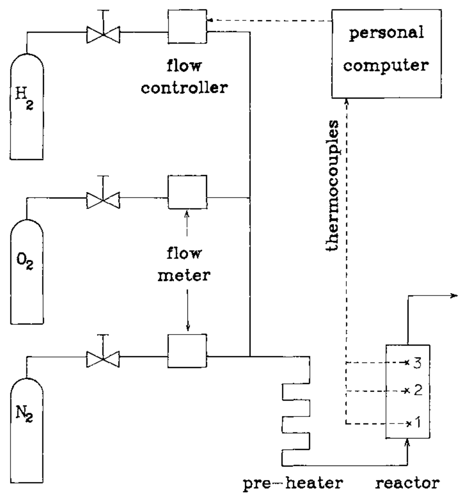

Fig. 1. Experimental apparatus

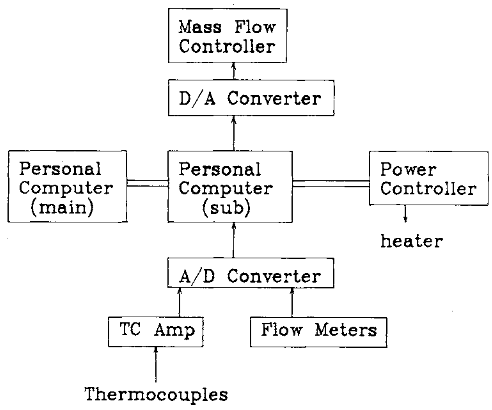

Fig. 2. Instrumentation diagram

2. The Fuzzy Controller

2.1 The basis of fuzzy control

The policies of the fuzzy controller are described by linguistic rules containing uncertain information. These rules are usually obtained from the knowledge of human operators and/or physical considerations. Linguistic rules, for example, take the following form:

IF "temperature is a little higher than a setpoint"

THEN "decrease the flow rate of the reactant a little,"

ELSE IF "temperature is far lower than a setpoint"

THEN "increase flow rate of the reactant a lot,"

ELSE ··· (1)

Here, the expressions such as "a little" and "a lot" have some vagueness and are thus suitable for fuzzy set description. In general, linguistic rules are translated into a set of fuzzy rules with some appropriate fuzzy sets. A fuzzy rule can be represented as an implication in the form of "IF A THEN B," where A and B are fuzzy sets. And the fuzzy controller is composed of fuzzy union of several fuzzy rules. From a certain input A', the controller estimates the output B'. A more detailed description of fuzzy-set theory appears in the **Appendix**.

2.2 The fuzzy controller algorithm

1) Universe of discourse The first task in the design of the fuzzy controller is to determine the primary fuzzy variables for the processes. Two input variables and one output variable are selected in the present work.

(i) e: Error, defined as the difference between the present maximum value of the catalyst temperature and the set point.

(ii) c: Change in error, defined as the rate of change of the value e during a sampling period.

(iii) u: Change in flow rate, defined as the change of the inlet reactant flow rate during a sampling period.

All fuzzy variables are quantized into 13 points and denoted in normalized form, ranging from -6 to 6, as shown in **Table 1**. To determine the universe of discourse for each variable, scaling factors Fe, Fc and Fu are introduced as follows:

Table 1. Scaling factor

Value	Element												
	−6	−5	−4	−3	−2	−1	0	1	2	3	4	5	6
PB	0	0	0	0	0	0	0	0	0	0.1	0.4	0.8	1.0
PM	0	0	0	0	0	0	0	0	0.2	0.8	1.0	0.7	0.2
PS	0	0	0	0	0	0	0.2	0.8	1.0	0.7	0.2	0	0
ZO	0	0	0	0	0	0.5	1.0	0.5	0	0	0	0	0
NS	0	0	0.2	0.7	1.0	0.8	0.2	0	0	0	0	0	0
NM	0.2	0.7	1.0	0.8	0.2	0	0	0	0	0	0	0	0
NB	1.0	0.8	0.4	0.1	0	0	0	0	0	0	0	0	0

$$\begin{aligned} e(Fe \times j) &= N(j) \\ c(Fc \times j) &= N(j) \\ u(Fu \times j) &= N(j) \end{aligned} \tag{2}$$

where j represents a quantized value of each variable and $N(j)$ represents grade of membership function of normalized form at point j. The real values of these scaling factors and ranges are shown in **Table 2**.

2) Linguistic values and fuzzy sets Each fuzzy variable has seven linguistic values: Positive Big, Positive Medium, Positive Small, Zero, Negative Small, Negative Medium and Negative Big. These values are abbreviated as PB, PM, PS, ZO, NS, NM and NB.

3) Membership functions The membership functions of these fuzzy values are defined in quantized form in Table 1. Values between the quantized points are linearly interpolated. The grade of membership function of fuzzy implication is specified by giving a value for each set of components e and c.

4) Control rules Using the above-mentioned definitions, the control rules are described as follows:

$$\text{IF } (e \text{ is NB}) \text{ AND } (c \text{ is ZO}) \text{ THEN } (u \text{ is PB})$$
$$\text{ELSE IF } \cdots \tag{3}$$

All rules used in this work are summarized in **Table 3**.

5) Translation of fuzzy outputs In this controller application, inputs and outputs are not fuzzy but are precise numerical values. So transformation between fuzzy and numerical values is needed. A numerical value can be considered as a special fuzzy set of which the membership function is zero except for one element. Fuzzy values are transformed to numerical values by use of the gravity center of the membership functions.

6) Implementation The adjustable parameters of this controller are scaling factors, fuzzy rules and shapes of membership functions. In most cases, fuzzy rules and membership functions are fixed. By varying the value of the scaling factors, the sensitivity of the controller can be adjusted. The ratio Fu/Fe corresponds to controller gain such as a proportional gain for the PID controller, though they are different in some points. Scaling factor influences the accuracy of observation as well as the sensitivity of manipulation. For example, the scaling factor can be considered as a sort of range of a multirange galvanometer. If the range is narrow, it is difficult to balance the meter. On the other hand, if the range is wide it is easy to balance the meter but accuracy is sacrificed.

Table 2. Control rules

	Range	Scaling factor
e	−25–25°C	4.2
c	−10–10°C	1.7
u	−3–3 ml/min	0.5

Table 3. Membership functions

c	e NB	NM	NS	ZO	PS	PM	PB
PB	PS	NS	NM	NB	NB	NB	NB
PM	PS	PS	NS	NM	NM	NB	NB
PS	PM	PS	ZO	NS	NS	NM	NB
ZO	PB	PM	PS	ZO	NS	NM	NB
NS	PB	PM	PS	PS	ZO	NS	NM
NM	PB	PB	PM	PM	PS	NS	NS
NB	PB	PB	PB	PB	PM	PS	NS

To represent the above-mentioned algorithm, a computer program is coded by the following flow:

i) Measure the current temperatures and calculate the numerical values of e and c.

ii) Infer the output fuzzy set u for each rule by using Mamdani's implication and Zadeh's composition rule of inference.

iii) Combine all the inference results in a fuzzy set.

iv) Convert the inference result to a numerical value by using the gravity center of the resulting fuzzy set.

v) Manipulate the flow controller for inlet hydrogen gas.

vi) Wait until the next sampling point and repeat the procedure above.

2.3 Results and discussion

An example of the start-up control experiments is shown in **Fig. 3**, where the catalyst temperatures at three locations and the flow rate of inlet hydrogen are plotted. At the beginning, all the catalyst temperatures are around 60°C, which coincides with the inlet gas temperature. Soon after the controller starts to work, the maximum temperature reaches 120°C. As can be seen in the figure, the controller works well, indicating negligible overshoot. During the initial period of control, the catalyst temperatures remain almost constant although the inlet hydrogen flow rate increases gradually. Around 300 seconds,

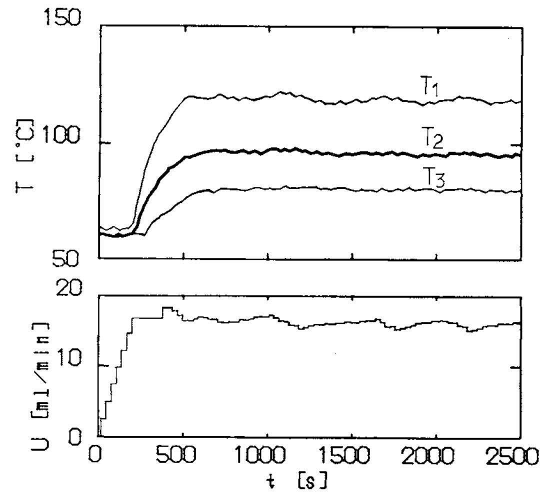

Fig. 3. Result by basic fuzzy controller

the temperatures abruptly start to rise naturally accompanied by ignition. Such nonlinear behavior is often seen in catalytic reaction systems, making it difficult to control such processes. After this period, the controller output gradually reduces its rate of increase.

The controlled temperatures of the catalyst indicate small fluctuations of low frequency. This is because of the very low sensitivity of the controller, which is designed not to produce a big overshoot in the period of start-up. In the present controller, controller gain can be varied by adjusting scaling factors, and thus the sensitivity of the regulator can be varied by its scaling factors. Usually these small fluctuations are not so significant. It is rather remarkable that the fuzzy controller can control the reactor start-up without overshootings.

3. The Modified Fuzzy Controller

3.1 Modification of the algorithm

To diminish a steady state error, decreasing a scaling factor *Fe* seems to be effective. For the start-up procedure, however, it incurs a danger of producing overshootings or oscillations because the scaling factor is so sensitive to the dynamical behavior of the closed-loop system. Thus automatic adjustment of the scaling factors is desirable. Considering the manner of control by a human operator, at the first stage he takes care of the upper digits of the thermometer to achieve a desired temperature. Once the temperature nears the target, he mainly pays attention to the lower digits of the meter. In other words, the operator changes his scope from macro to micro scale. On analogy to such operation, the main concept of the automatic adjustment mechanism is based on a simple idea such as "If error is large, then let scaling factor be large and vice versa."

To realize this consideration, a simple performance index $i(k)$ is defined as

$$i(k)=\{e(k)^2+e(k-1)^2+e(k-2)^2\}/3 \qquad (4)$$

According to the performance index, the scaling factors are adjusted as follows:

$$Fx(k)=C(k)Fx_0 \qquad (5)$$

where x is a replacement of e or c, and x_0 is an initial value of x. $C(k)$ is a modification coefficient defined as

$$C(k)=\begin{cases} 1.0 & \text{for } i_1 \le i(k) \\ 0.5 & \text{for } i_2 < i(k) < i_1 \\ 0.2 & \text{for } i_3 < i(k) \le i_2 \\ 0.1 & i(k) \le i_3 \end{cases} \qquad (6)$$

This coefficient also may be expressible in linguistic forms:

"IF $i(k)$ is very large THEN $C(k)$ is very big ELSE

IF $i(k)$ is large THEN $C(k)$ is big ELSE

IF $i(k)$ is medium THEN $C(k)$ is medium ELSE (7)

IF $i(k)$ is small THEN $C(k)$ is small."

The numerical definition of the coefficient can be thought of as a special case of fuzzy representation. For simplicity, numerical representation was used in the experiment. The value of i_1, i_2 and i_3 are determined by taking account of the performance of the basic fuzzy controller. In this work, these values are selected as 150, 40 and 10, respectively.

3.2 Results and discussion

An example of experimental control by the modified controller is shown in **Fig. 4**. The experimental condition is the same as in Fig. 3. In this case the steady state error is almost invisible and the start-up performance is also satisfactory. At the bottom of the figure the value of scaling coefficient is plotted. It can be seen that the factor is adjusted as expected.

To check the regulation performance and stability of this controller, response to a disturbance was tested, with the results shown in **Fig. 5**. Around 1250 seconds, the flow rate of inlet nitrogen gas is abruptly decreased from 800 to 600 ml/min. Influenced by the change of flow rate, catalytic temperatures increased suddenly but then settled down to the set-point in a few minutes. The scaling coefficient is also changed after the disturbance.

Conclusion

Experimental application of a fuzzy control algorithm to the control of an exothermic catalytic reactor is examined. Even a simple fuzzy controller was able to control the start-up of the reactor without

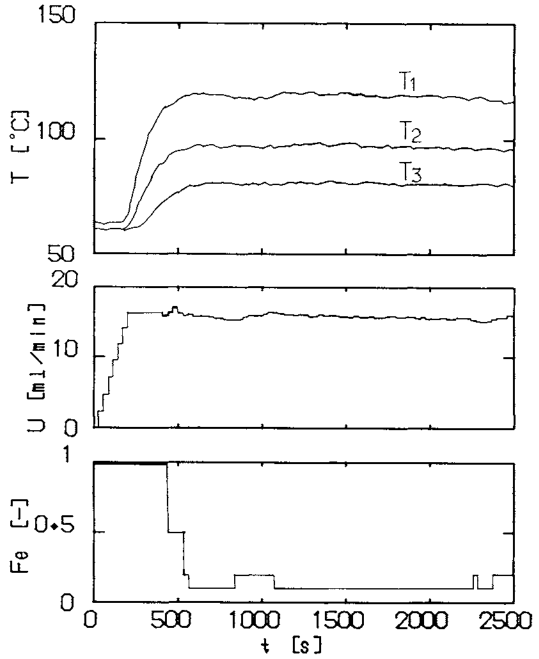

Fig. 4. Result by improved controller

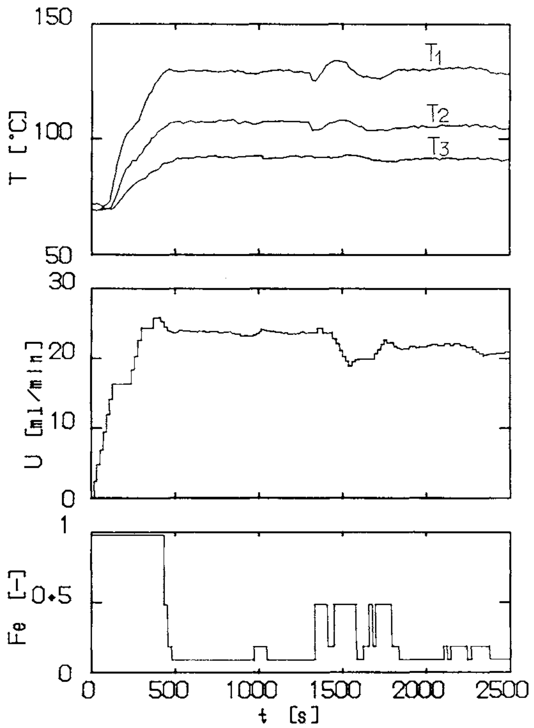

Fig. 5. Response of controlled process under a step disturbance

overshootings.

Automatic adjustment of scaling factors for the discourse of universe of membership functions was also tested. It was shown that this adaptive mechanism works well to reduce the error around the steady state.

Through the work, it was demonstrated that start-up control of the reactor can be satisfactorily controlled on the basis of the fuzzy algorithms. It is worth noting that only simple *a priori* information is used to construct the control rules. Since the algorithm is easily modified, the fuzzy control scheme can be applied to more complex processes, mathematical models of which are hard to construct.

Appendix

Fuzzy set theory

A short mathematical description of fuzzy set theory is presented here. It covers only a part of the theory related to the fuzzy controller mentioned in this paper.

A fuzzy set A on a universe of discourse U is defined by its membership function $m_A(x)$, which indicates the degree of belonging to A for each element x. The grade of membership function for each element is in the interval [0, 1].

Basic calculations for fuzzy sets A and B are defined by their membership functions, for example, as follows:

1) NOT:

$$m_{\neg A}(x) = 1 - m_A(x) \tag{A-1}$$

2) OR:

$$m_{A \cup B}(x) = \max[\mathrm{m}_A(x), m_B(x)] \tag{A-2}$$

3) AND:

$$m_{A \cap B}(x) = \min[\mathrm{m}_A(x), m_B(x)] \tag{A-3}$$

And fuzzy rules are stated as follows:

$$\begin{array}{l}\text{“IF } A_1 \text{ THEN } B_1 \\ \text{OR IF } A_2 \text{ THEN } B_2\text{”}\end{array} \tag{A-4}$$

Here, each statement corresponds mathematically to fuzzy implication. Among various definitions of implication operator, we use this simple fuzzy relation:

$$m_{A \to B}(x, y) = \min[\mathrm{m}_A(x), m_B(y)] \tag{A-5}$$

Fuzzy inference is a process for calculating the output from fuzzy conditional statements when a certain input condition is given. This calculation is defined by the compositional rule of inference. IF an input A' is given, the inferred output B' under the condition "IF A THEN B" is defined as

$$m_{B'}(x) = \max[\min[m_{A'}, (x), m_{A \to B}(x, y)] \tag{A-6}$$

Nomenclature

A, B	=	fuzzy sets	[—]
C	=	modification coefficient	[—]
c	=	change in error	[—]
e	=	error in temperature	[K]
Fe, Fc, Fu	=	scaling factors	[—]
i	=	performance index	[K^2]
i_1, i_2, i_3	=	boundary performance indexes	[K^2]
m	=	membership function	[—]
N	=	normalized membership function	[—]
t	=	time	[s]
T_i	=	temperature at location i	[°C]
U	=	reactant flow rate	[ml/min]
u	=	change in reactant flow rate	[ml/min]

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RADIAL AND VERTICAL DISTRIBUTIONS OF THE INTERSTITIAL GAS VELOCITY IN A FLUIDIZED BED

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Key Words: Fluidization, Interstitial Gas Velocity, Emulsion Phase, Leakage Factor, Measuring Technique, Optical Fiber

The radial and vertical distributions of the interstitial gas velocity in a fluidized bed of group B particles were measured over a wide range of superficial gas velocity by applying the optical fiber technique with ozone used as tracer gas. The bed materials were sand particles, $d_p=184\,\mu$m, and alumina beads, $d_p=250\,\mu$m.

The interstitial gas velocities in the jet region were found to be higher than those predicted by the ideal two-phase postulate. This increase reached 30% and 20% of (U_o-U_{mf}) for sand particles and alumina beads respectively. These velocities decreased with height above the distributor, approaching those at incipient fluidization near the bed wall but taking still higher values at mid-points.

The leakage factor K calculated from the observed interstitial gas velocity was compared to that predicted by a recently developed bubble simulator which was inherently based on the observation of radial and vertical distributions of size and frequency of bubbles, and good agreement was obtained.

Introduction

It is essential in fluidized-bed reactor modeling and simulation to predict how the fluidizing gas fed into it is divided into bubble and interstitial phases. We may intuitively assume that the gas in the interstitial phase is much more effective in bringing about chemical reaction between gas and solid so that wrong prediction of this division may result in significant error in the calculation of reaction performance.

The well-known ideal two-phase postulate is usually formulated as

$$Q_B/A=U_o-U_{mf} \tag{1}$$

i.e., the gas flowing in the dense phase is that at U_{mf}, and the gas in excess forms a visible bubble flow. Equation (1) has been questioned and a great deal of experimental work indicates that this postulate largely overestimates the visible bubble flow rate.[1,4,14,15,17] To account for this discrepancy, Eq. (1) is written as

$$Q_B/A=U_o-KU_{mf} \tag{2}$$

The values of the leakage factor K were summarized by Grace and Clift[6] based on a number of works which allowed direct measurement or estimation of the visible bubble flow rate. K was found to vary from system to system and, within a given system, is dependent on height and superficial gas velocity. In the literature, there is controversy on the cause of the observed discrepancy between Eq. (1) and the experimental results represented by Eq. (2).

Rowe *et al.*,[16] using an X-ray technique deduced that the interstitial gas flow is much greater than U_{mf}, say, 10 to 25 times in a bed of sand particles of average diameter $52\,\mu$m. Although this technique does not disturb the flow in the bed, it cannot be applied to the measurement of the local interstitial gas velocity. Kawanashi and Yamazaki[12] used oxygen sensors to detect oxygen which was used as tracer gas in a bed of cracking catalyst, $d_p=60\,\mu$m, fluidized by nitrogen, and concluded that the interstitial gas velocity is larger than U_{mf} and decreases with height above the distributor. But their oxygen sensors were

Received September 5, 1987. Correspondence concerning this article should be addressed to M. Ishida.